# A FRAMEWORK FOR THE PREDICTION OF SOIL MOISTURE

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## ABSTRACT

Through its influence on the mobility of troops and materiel, the interaction between weather and landscape is of primary importance to the effectiveness and timeliness of Army operations. More specifically, knowledge of the spatial and temporal variability in soil moisture over large areas, at the scale of tactical operations (~100 m), has the potential to dramatically improve trafficability assessments. The majority of Army operations are conducted in regions where field observations of soil moisture are sparse in space and/or time or completely unavailable. However, remotely sensed information about the factors that affect the spatial variability in soil moisture over a range of spatial scales are available. We present here a framework by which we can fuse these remotely sensed data representing the various factors affecting soil moisture through the existing tRIBS hydrologic model to produce forecasts of the spatial distribution of soil moisture. Using data assimilation techniques these forecasts can be dynamically updated when remotely sensed observations of soil moisture using become available. When used in conjunction with tactical decision aids, such as IWEDA, the proposed fusion of data through tRIBS has the potential to improve trafficability assessments and other soil moisture dependent Army operations.

## 1. INTRODUCTION

The interaction between weather and the land surface is a limiting factor in the effectiveness and timeliness of Army operations. In particular, soil moisture is a dynamic land surface state variable that reflects the interaction between precipitation and the hydrologic response of a basin and influences the ease of troop and vehicle movement.

Army applications require information on soil moisture to forecast trafficability for tactical vehicles, ground force deployment, and mission logistical approach. Tactical decision makers can more readily determine possible enemy or friendly lines of approach with the aid of detailed and thorough trafficability assessment. For example, moisture from the surface to 5 cm in depth is important for surface traction, while moisture from 5-10 cm in depth impacts light armor vehicle speed, and moisture from 10-30 cm can impact multiple pass trafficability for tanks. Moisture from 30-80 cm in depth affects large scale operations. Furthermore, soil moisture is also important to predict river stage and reservoir volume, as well as forecast flood crests and low flows, flash-flood risk in small catchments, and low-level fog formation. From the warfighter's perspective, characterization of the surface soil moisture is also critical to electro-optical weapon systems navigation, and mine placement and detection.

Presently, assessment of trafficability is often done through analysis of field-based soil moisture measurements at points within a region. However, Entekhabi et al. (1996) concluded that these point scale data represent the soil moisture only in very localized areas. The influence of local microtopography, soils and vegetation, all of which demonstrate significant spatial heterogeneity, make interpretation of these localized measurements difficult from the perspective of trafficability over broader regions. Near surface soil moisture is remotely sensed by a number of operational satellites, but at coarse spatial scales and long temporal intervals from the perspective of Army operations.

Using models to predict the spatial distribution of soil moisture at operational spatial scales (~100 m), and how it changes over operational time scales can improve trafficability assessments. Soil-vegetation-atmosphere transfer (SVAT) models (e.g., Peters-Lidard et al., 1997) can predict soil moisture in a dynamic and spatially distributed fashion over large regions, but at resolutions that are too coarse for detailed trafficability assessment (e.g., 1 km). Furthermore, these SVAT models are unable to capture the role of topography in redistributing soil moisture in the saturated and unsaturated zones. Distributed watershed hydrology models have physically based parameterizations to model the redistribution of soil moisture in the subsurface, but need to be constrained to observations to reduce the uncertainty in the forecast.

We present here a framework to forecast soil moisture at operational scales by assimilating observations of remotely sensed soil moisture data with a distributed watershed hydrology model. When combined with empirical models to predict remold cone index (RCI) as a function of soil moisture and properties, a map of RCI can be produced which can then be considered against the vehicle cone index (VCI) for a particular vehicle type. In similar fashion to the Integrated Weather Effects Decision Aid (IWEDA) program, the end product of this framework is a time-evolving map of Green/Amber/Red conditions for a particular vehicle type,

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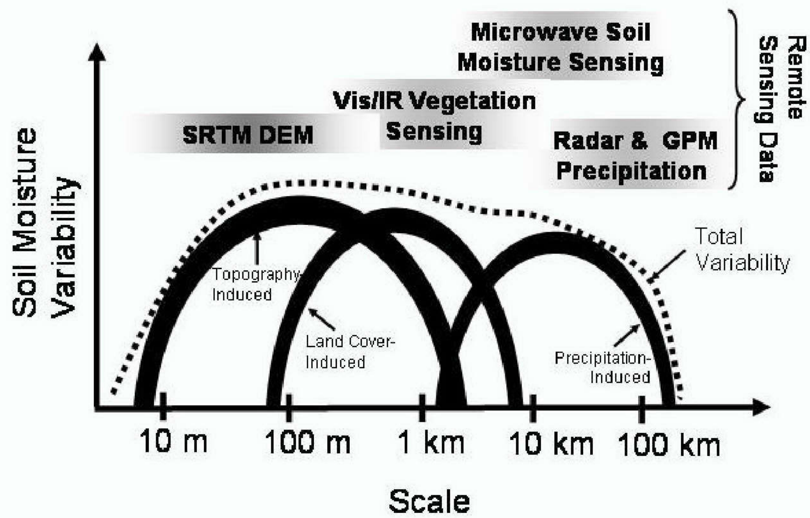


Fig. 1: Soil moisture variability is effected by several factors which act over varying spatial scales, but each of which have corresponding sources of remotely sensed data.

but at spatial scales of tactical decision making. In the following we discuss the role of topography, vegetation and precipitation in the spatial distribution of soil moisture. This is followed by an outline of the distributed hydrologic model we employ to simulate soil moisture through space and time. The fusion of remotely sensed soil moisture data with the hydrologic model through a data assimilation framework is subsequently addressed. Finally, we present potential applications of this work to produce trafficability assessments at tactical operation scales.

## 2. FACTORS AFFECTING SOIL MOISTURE

Soil moisture is a land surface variable which links global water, energy, and biogeochemical balance. As such, the distribution of soil moisture at a point changes through time is a function of several factors acting across a range of spatial and temporal scales (Rodriguez-Iturbe et al., 1995; Schmugge and Jackson, 1996). Among the more important factors affecting the spatial variability of soil moisture are topography, vegetation, and precipitation. Fig. 1 demonstrates the influence these factors have on the distribution of soil moisture at their characteristic scales. While presumably, there exists some scales over which the effects of multiple factors can overlap, remotely sensed data corresponding to each source of variability can provide information in inaccessible locations and across extensive domains. Merging these data to develop value-added products which aid in trafficability assessments at tactical operation scales is the primary focus of this work. Hence, understanding how these data affect soil moisture observation and modeling are critical developments to this work.

Fundamentally, precipitation delivers moisture to a basin. When viewed as spatial fields over extensive domains, precipitation events may drastically range in size or exhibit two orders of magnitude of internal variability. Soils, landuse and vegetative cover impact soil moisture through their influence on the redistribution of water in the subsurface and the depletion of water from storage through evapotransipration. Topography also serves as a control on the lateral redistribution of water in the subsurface by providing gravitational potential for flow through porous media. Vegetation, landuse and macroscale variation in soil characteristics affect soil moisture variability over domains ranging in size from hundreds of meters to tens of kilometers. However, local topography controls soil moisture variability at spatial scales critical to detailed trafficability assessments.

The redistribution of water in the subsurface has been previously shown to occur preferentially in a downslope direction, underscoring the importance of adequate representation of topography in soil moisture modeling. In particular, the downslope movement of water in soils with sloping layers will be proportional to the slope itself and the vertical flux of water in the subsurface (Zaslavsky and Sinai, 1981). Furthermore, as shown by Yeh et al. (1985a,b,c) for randomly interbeded layers of soil with different textures, the horizontal hydraulic conductivity can be up to six orders of magnitude greater than the

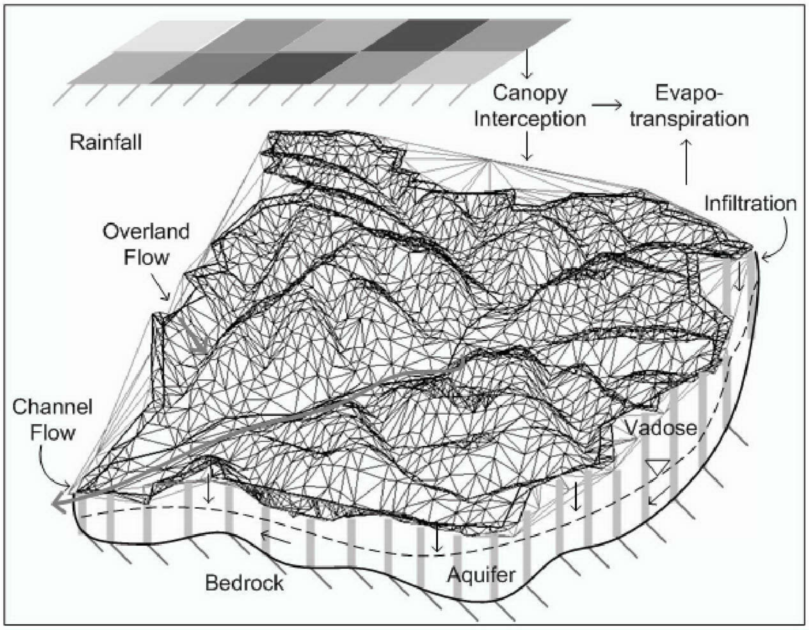


Fig. 2: A conceptual diagram of the tRIBS model framework, and the hydrologic processes it encompasses.

vertical hydraulic conductivity. When considered together, these factors demonstrate that moisture in the subsurface moves preferentially away from ridges toward valley bottoms (Famiglietti et al., 1998; Western et al., 1999). Topographic position, hydraulic properties of the soil, and its wetting-drying history thus control the spatial patterns in soil moisture.

### 3. HYDROLOGIC MODEL OUTLINE

To simulate the response of the land surface to spatially distributed high-resolution precipitation data we employ a distributed parameter hydrologic computer model which uses a geographic information systems (GIS) representation of a watershed and its physical attributes as a computational surface. The computational surface used by the model is a triangular irregular network (TIN), which allows for representation of basin topography at multiple scale resolutions. The TIN-based Real-time Integrated Basin Simulator (tRIBS) is a fully distributed, physically-based, dynamic basin hydrology computer model that takes as input readily available geospatial data. A full description of the tRIBS model and its application to several test basins is discussed in detail by Ivanov et al. (2004), but a brief introduction to the model is provided here. A schematic diagram shows processes incorporated into the tRIBS model as well as a representation of the TIN-based computational surface (Fig. 2).

As previously mentioned tRIBS relies on a triangulated irregular network and its associated Voronoi (or Thiessen) polygon mesh as its computational surface. The TIN framework allows the user to preserve important topographic characteristics such as individual ridges and valleys at fine resolutions while allowing planar regions to be represented at coarser resolutions. The advantage of such a computational surface is that fine-scale features are preserved without spending equal computer processor resources on regions with relatively homogeneous topography. Intersections of the TIN mesh, which correspond to the centroid of each Voronoi polygon, comprise the computational nodes. The region bounded by the Voronoi polygon and the soil column represents a finite-volume element, with interfaces between adjacent Voronoi cells serving as control surfaces through which fluxes are calculated. tRIBS includes physically-based parameterizations describing the processes of canopy interception, evapotranspiration, infiltration, lateral redistribution of soil moisture, and runoff routing in a spatially explicit fashion.

Canopy interception is accomplished using a model that relies on species dependent retention capacities (Rutter et al., 1971, 1975). Drainage from the canopy is accounted for following Shuttleworth (1979). Evapotranspiration, as well as latent, sensible, and ground heat fluxes are modeled using energy budget methods.

Evapotraspiration from bare soil and vegetated surfaces is limited by soil water content in the top soil layer and root zone. A kinematic approximation for unsaturated flow (Cabral et al., 1992, Garrote and Bras, 1995) underlies the infiltration method of tRIBS, and different parameterizations are used for ponded and unsaturated infiltration.

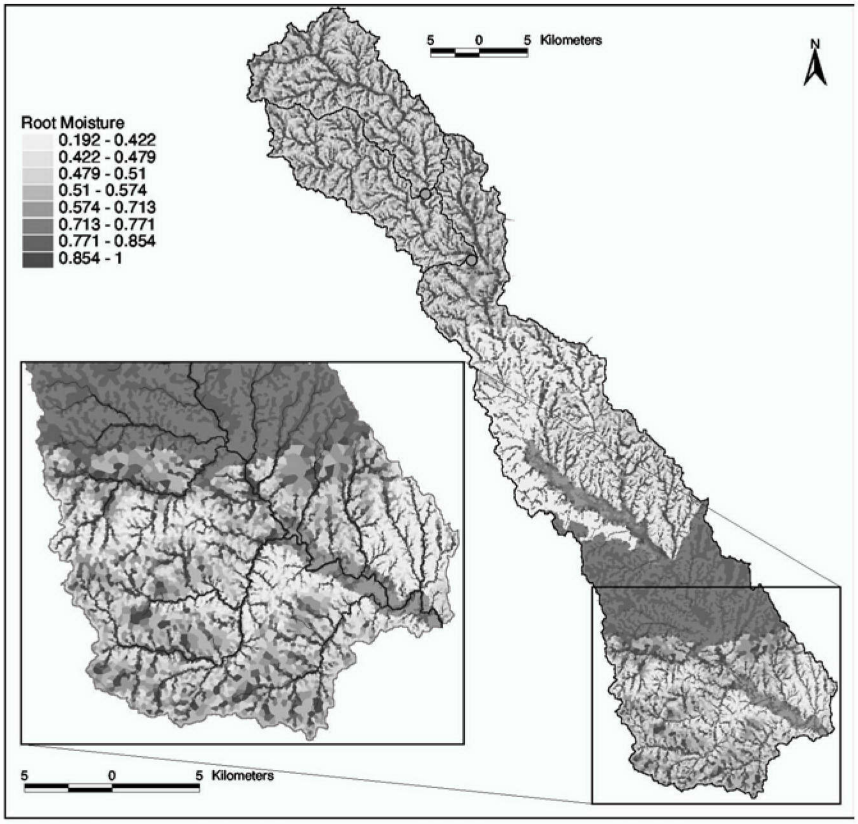


Fig. 3: Mean soil moisture content in the top 1 m of soil over a 7-year simulation for the Blue River basin, OK.

Lateral redistribution of soil moisture in the unsaturated zone occurs during both storm events and interstorm intervals. Lateral fluxes in the saturated zone are computed using an approach that explicitly routes flow in a cell-to-cell fashion. Within a cell saturation excess runoff and groundwater return flow are generated by considering the difference between influx and outflux of water within each finite volume cell at each timestep.

Infiltration excess runoff is generated when the throughfall exceeds infiltration capacity, and perched subsurface storm flow occurs when water from the unsaturated zone of a cell is discharged onto the surface of the downslope neighbor. Reinfiltration of runoff is not considered. Overland flow at a computational element is partitioned into hillslope runoff and channel runoff. Travel times of hillslope runoff are computed using a velocity parameter that must be calibrated for individual watersheds. Channel runoff is routed using the kinematic wave equation, assuming channels have approximately rectangular cross-sectional geometries and that the Manning equation is valid.

As input, tRIBS requires digital elevation models (e.g., USGS NED, SRTM, etc.), soil data (e.g., STATSGO, etc.), land use/land cover (e.g., NLCD, etc.), initial water table elevations (e.g., following Sivapalan et al., 1987), precipitation data (e.g., NEXRAD, etc.), and meteorological data (e.g., temperature, etc.).

The output of a tRIBS simulation for soil moisture applications is a map showing the soil moisture in each Voronoi cell at a particular timestep in the simulation (Fig. 3). In a later section we present a framework for translating this map of soil moisture into a map of Green/Amber/Red zones for a particular vehicle.

Ivanov, et al. (2004) demonstrated tRIBS capability of discerning the role the relationship between topography and the frequency of occurrence of different runoff generation mechanisms for regions within the Blue River basin characterized by different groundwater dynamics. Each panel in Fig. 4 shows the frequency of occurrence of a particular runoff generation mechanism versus the so-called topographic index, $\ln(A/\tan\beta)$, where $A$ is the contributing drainage area to a point, and $\tan\beta$ is the local ground surface slope. Larger values of $\ln(A/\tan\beta)$ are associated with a tendency for greater soil moisture. The different markers in the plots of Fig. 4 group dominant groundwater dynamics regions. All four panels in Fig. 4 show that frequency of occurrence of the different runoff

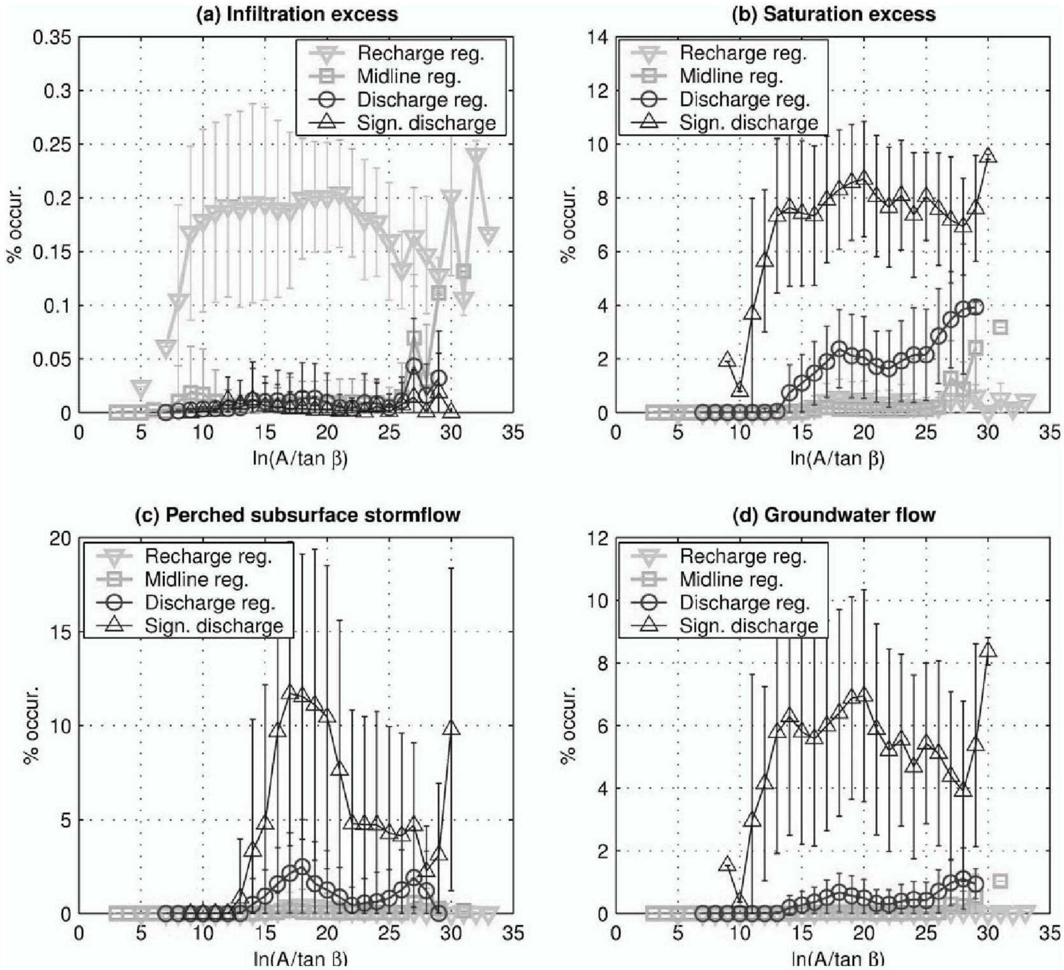


Fig. 4: Frequency of occurrence of four different runoff generation mechanisms in the Blue River basin, OK: (a) infiltration excess, (b) saturation excess, (c) perched subsurface stormflow, and (d) groundwater flow.

generation mechanisms depends on the local topographic characteristics. Fig. 4(a) shows that infiltration excess runoff is generated in regions serving to recharge the groundwater aquifer. However, the propensity to have infiltration excess in the recharging regions is likely the result of the soils being composed of predominantly clays and silts in those regions (Ivanov et al., 2004). The frequency of occurrence of runoff generation mechanisms in Figs. 4(b),(c), and (d), which all require a saturated ground surface, is highest in regions acting as a source of significant groundwater discharge (Ivanov, et al., 2004). However, the frequency of occurrence of perched subsurface stormflow and groundwater flow exhibits a wider range of variability than the frequency of occurrence of the other two runoff generation mechanisms. These results depict the ability of the tRIBS model to depict the spatial distribution of the relevant runoff generation mechanisms and its relationship to topography and groundwater dynamics.

## 4. SOIL MOISTURE DATA ASSIMILATION AND FUSION

### 4.1 Remotely sensed soil moisture data

Soil moisture strongly influences the emission of low frequency microwave radiation. In particular, the emissivity of soils varies from approximately 0.6 for wet soils to 0.9 in dry soils in the L-band (~ 1.4 GHz) of the spectrum (Njoku and Entekhabi, 1996). This wide range of emissivity values for soils translates to a dynamic range in the radiobrightness temperature observed by microwave radiometers that is larger than the radiometer's noise sensitivity. Passive microwave remote sensing of soil moisture is a direct benefit of this large signal-to-noise ratio (Njoku and Entekhabi, 1996). Greater vegetation penetration and lessened atmospheric attenuation at longer wavelengths makes the low-frequency microwave range of 1-3 GHz (30-10 cm wavelength) best suited to soil moisture sensing (Njoku and Entekhabi, 1996).

Several complications, however, make obtaining remotely sensed soil moisture observations difficult. Specifically, the required antenna size to sense soil moisture at spatial scales appropriate to trafficability assessment is problematic when sensing at lower frequencies. NASA developed the Electronically Scanned Thinned Array Radiometer (ESTAR) concept to, among other tasks, sense soil moisture at a single frequency (1.4 GHz). The ESTAR sensor could potentially provide soil moisture data at a scanning swath width of approximately 1200 km, ground spatial resolution of approximately 40 km and global mapping capability every 3 days (Levine et al., 1989; Swift, 1993). However, real-time ground military operations are only partially supported by soil moisture assessment at these spatiotemporal resolutions. Other space-born passive microwave sensors, operating at high 6.6-30GHz frequencies (Gloersen and Barath, 1977; Hollinger et al., 1990; Kummerow et al., 2000), as well as currently planned L-band sensors (Njoku et al., 1999) may provide data at ground spatial resolutions ranging from 10 to 100 km. A more effective use of these data would be to fuse them with modeled soil moisture data through the tRIBS model to produce value-added trafficability assessment aids.

**4.2 Data fusion and assimilation**

Two important sources of estimates of soil moisture have been described here: (1) the soil moisture state evolved by tRIBS through time, and (2) remotely sensed observations of near surface soil moisture taken at a particular instant in time. These two distinct forms of soil moisture state estimation carry uncertainty associated with their respective sources.

The evolved soil moisture estimate is subject to what is commonly referred to as model uncertainty. This uncertainty arises from, among other sources, the parameterization of the various hydrological processes, uncertainty in parameter values, numerical round-off error, and discretization of the land surface into a computational surface. On the other hand, the remotely sensed observations of soil moisture are subject to so-called observational or measurement uncertainty. This is uncertainty that is attributed to the sensitivity of the microwave radiometer, data retrieval from the satellite, and retrieval in the estimation of soil moisture from the radiobrightness temperature.

Using optimal estimation theory that is well established in the hydrologic sciences, we can produce an optimal estimate of the soil moisture state by fusing the remotely sensed observations of soil moisture with the evolved soil moisture estimate from tRIBS. This soil moisture state estimate is optimal in the sense that it is a minimum error estimate produced as a combination of the model and observational estimates, each weighted by its associated uncertainty (Gelb, 1974).

Specifically applied to this work, the tRIBS model propagates the soil moisture state given hydrometeorological forcing such as precipitation, temperature and cloudiness. An algorithm is used to translate the soil moisture state evolved by tRIBS to microwave radiobrightness temperatures retrieval when remotely sensed observations of the soil state become available. Existing grey body radiative transfer models (e.g., Ulaby et al., 1986, Galantowicz et al., 1999) are examples of algorithms that could be implemented in the tRIBS model.

An additional step is required to resolve the inconsistency between the spatial scales at which tRIBS simulates soil moisture (10 – 500 m) and those at which space-born radiometers typically observe soil moisture (10 – 100 km). This inconsistency of spatial scales is overcome through the use of optimal downscaling (i.e. transfer of information from larger to smaller spatial scales) procedures. Previous work has successfully developed procedures to accomplish four-dimensional soil moisture data assimilation into a hydrologic model (Reichle et al., 2001, 2002).

Complete implementation of data assimilation frameworks can be frustrated by the large dimensions of a problem such as the one being considered. Producing estimates that preserve the benefits of merging model forecast information with observational data, but which are not necessarily statistically optimal, is one way this problem can be overcome. Such estimates are known as suboptimal solutions. This approach is known as a data fusion technique. The desired outcome of this work is to produce a combined data fusion and assimilation mechanism that can interface with modular models elements developed in this or other projects, include both dynamic and static sources of information, and be applied to models of large dimension and computational demand.

## 5. TRAFFICABILITY AND SOIL MOISTURE

Translating the estimated soil moisture state into an actionable variable from the perspective of Army operations requires several additional steps. The first involves combining soil properties with the soil moisture state estimate to produce a variable related to soil strength and bearing capacity.

One common method of measuring in situ soil strength is through the use of a soil profile cone penetrometer (PCP). The PCP is a field instrument comprised of slender rod approximately one meter in length with a cone shaped end that measures the compressive and frictional resistance of the soil as the

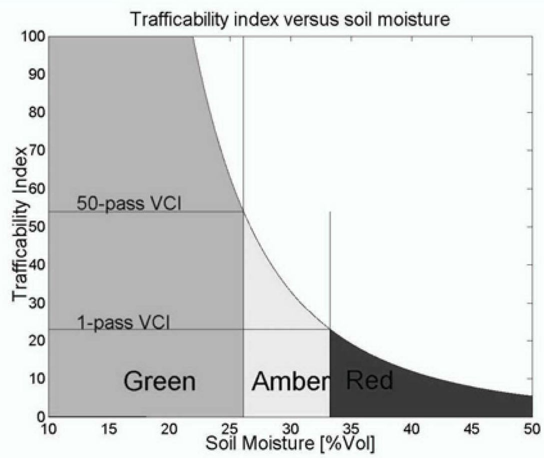


Fig. 5: Trafficability index (RCI) versus volumetric soil moisture. For the M1A2 Abrams, green-amber threshold is based on 50-pass VCI, and amber-red threshold for 1-pass VSI.

PCP is forced vertically downward into the soil column. This resistance, typically reported in units of force per unit area, is referred to as the cone index (CI). Multiplying CI by a measure of soil remoldability, produces the remold cone index (RCI) which is a function of the soil density, type and moisture content (Mason, 2004). Empirical data suggests that RCI tends to decay with increasing soil moisture, and is sensitive to cumulative rainfall (Mason, 2004). Although the relationship varies by vehicle, RCI is closely related important tactical variables such as vehicle average speed and momentum (Mason, 2004).

Using data from Sullivan and Anderson (2000) we have developed an algorithm by which RCI can be predicted given one of eight soil classes, and a value of soil moisture. This algorithm can be implemented into tRIBS to produce an estimate of RCI at each computational node within the basin being considered, given the soil moisture and properties at that computational node, at each timestep of the simulation. Such an estimate of RCI can then be considered against the tolerable values of vehicle cone index (VCI) for a particular vehicle type. For example, Fig. 5 depicts trafficability index (RCI) versus soil moisture for a clayey soil. Considering the 1-pass and 50-pass VCI for the M1A2 Abrams allows the delineation of Green/Amber/Red thresholds based on soil moisture. Along with other landscape variables important to vehicle trafficability such as local topographic slope, and landuse or vegetative cover, the spatial distribution of RCI developed from the soil properties and moisture can be implemented in an IWEDA-like framework. The result would be a map of Green/Amber/Red conditions at each tRIBS computational node throughout a simulated region.

## CONCLUSIONS

Soil moisture is a dynamic land surface variable that demonstrates significant spatial variation as a function of variability in soils, vegetation and landuse as well as topographic position. Through its relationship to soil strength and bearing capacity, soil moisture is a limiting factor the spatial scope and timing of Army operations. Conversely, knowing the evolution of soil moisture characteristics of a region at time and space scales of tactical operations (~100 m) has the potential to dramatically improve trafficability assessments. We present a framework by which to fuse remotely sensed soil moisture products with the soil moisture state evolved by a distributed parameter hydrologic model to produce value-added products to aid in detailed trafficability assessment of Army operations. This framework involves dynamically updating the soil moisture field evolved by the tRIBS model when remotely sensed soil moisture observations become available using well established data assimilation procedures. The net effect of this fusion of models in data is to combine information about soil moistures from independent sources to reduce the uncertainty in the estimate of the soil moisture state. Through models that relate remold cone index (RCI) to soil classification and moisture, the spatial distribution of soil moisture can be translated into the spatial distribution of RCI. Then, when considering the spatial distribution of RCI against the vehicle cone index (VCI), an actionable map of Green/Amber/Red conditions throughout a given region can be produced.

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